[Article] Optimizing the design of a plug-in hybrid electric vehicle from the early phase: an advanced sizing methodology

(Article begins on next page)

Taylor & Francis
Taylor & Francis Group

Computer-Aided Design and Applications

ISSN: (Print) 1686-4360 (Online) Journal homepage: http://www.tandfonline.com/loi/tcad20

Optimizing the design of a plug-in hybrid electric vehicle from the early phase: an advanced sizing methodology

Federico Millo, Jianning Zhao, Luciano Rolando, Claudio Cubito & Rocco Fuso

To cite this article: Federico Millo, Jianning Zhao, Luciano Rolando, Claudio Cubito & Rocco Fuso (2015) Optimizing the design of a plug-in hybrid electric vehicle from the early phase: an advanced sizing methodology, Computer-Aided Design and Applications, 12:sup1, 22-32, DOI: 10.1080/16864360.2015.1077072

To link to this article: http://dx.doi.org/10.1080/16864360.2015.1077072

Published online: 28 Aug 2015.

COMPUTER-AIDED DESIGN & APPLICATIONS, 2015
VOL. 12, NO. S1, 22–32
http://dx.doi.org/10.1080/16864360.2015.1077072

Optimizing the design of a plug-in hybrid electric vehicle from the early phase: an advanced sizing methodology

Federico Millo, Jianning Zhao, Luciano Rolando, Claudio Cubito and Rocco Fuso

Politecnico di Torino

ABSTRACT

A plug-in hybrid electric powertrain, as one of the most promising solutions to increase the fuel economy and to meet the stringent requirements of low emissions urban zones, has been investigated and developed for a light duty commercial vehicle application in this work. The plug-in hybrid electric powertrain combines an advanced small diesel internal combustion engine with a high energy battery pack, capable to assure an extended range in pure electric mode for specific areas, like the low/zero emissions urban zones. Since the right size of the powertrain components is essential to fully exploit the benefits of the hybridization, an advanced methodology has been proposed to optimize the design of the plug-in hybrid powertrain at an early phase. This methodology is based on the genetic algorithm approach for the choice of the powertrain component characteristics, combined with a quasi-optimal energy management strategy that is the Equivalent fuel Consumption Management Strategy (ECMS). The performance of the hybrid electric powertrain which was designed through the proposed methodology were then assessed and analyzed over the Worldwide Harmonized Light Duty Driving Cycle (WLTC) by means of a simulation model, thus demonstrating its effectiveness in addressing the issue of the powertrain components sizing from the early stage of the design process.

KEYWORDS
Plug-in hybrid electric vehicle; genetic algorithm; energy management

1. Introduction

In a context of growing demand for sustainable transportation worldwide [14], different technical solutions for Hybrid Electric Vehicles (HEVs) are nowadays being investigated as effective ways to improve the efficiency of conventional powertrains and thus to reduce their fuel consumption and CO_2 emissions [5].

Furthermore the possibility to combine pure electric operation within Low Emission Zones (LEVs) with the range capabilities of conventional vehicles makes plug-in Hybrid Electric Vehicles (pHEVs) the stepping stone towards the development of the electric mobility.

On the other hand, hybridization introduces extra costs and complexities related to the vehicle design. As a matter of fact HEVs performance can be strongly affected by the selected powertrain architecture, by the component size and by the powertrain control strategy [19],[15].

Several approaches concerning the optimization of hybrid powertrains have been already described in scientific literature [7], but most of them are focused either on the optimization of the electric machines [8],[29] or of the Internal Combustion Engine (ICE) [9], or of the battery [20], or of the powertrain control strategy [22],[25] and lack of an overall perspective.

Therefore, the aim of this paper is to describe a comprehensive methodology to design a hybrid powertrain architecture, the features of its main components, and the Energy Management System (EMS) in a global and interactive perspective, from the early phase of the design process.

After a brief overview on the HEV design (section 2), the proposed methodology focusing on the optimization algorithms used to size the powertrain components (section 3) and to develop the Energy Management will be discussed. Then the powertrain architecture selected in this study for a light duty commercial vehicle will be described in section 4. The main findings of this analysis will be presented in section 5, where sensitivity analysis results will also be shown to prove the robustness of the proposed methodology.

2. Design of a plug-in hybrid electric vehicle

Generally speaking the powertrain of a HEV is composed by an Internal Combustion Engine and by one or more Electric Machines (EMs), which are usually powered by a battery. Therefore, once the mission of the vehicle has been defined, the design of the hybrid powertrain has to

CONTACT Federico Millo federico.millo@polito.it

deal with:

- the choice of the architecture (i.e. series or parallel);
- the sizing of its main components (i.e. power/energy of ICE, Electric Machines (EMs) and battery);
- the definition of a suitable energy management strategy.

The vehicle class and the vehicle typical mission allow defining the most suitable powertrain architecture. For example a Range Extended Electric Vehicle (RE-EV) could represent the most valuable choice for a city car, since it mainly operates as an Electric Vehicle, while the internal combustion engine is only exploited to increase the range capability [11]. On the other hand, a parallel architecture could be more suitable for heavier vehicles, such as a Sport Utility Vehicle (SUV), where the combination of ICE and electric machine has to be exploited. The former is typically the main power actuator, while the latter is generally utilized to enhance the average efficiency of the powertrain system.

Finally the control algorithm used for the energy management should be able to achieve performance as close as possible to the optimality and it should be at the same time implementable in a real Engine Control Unit (ECU) [2], [3].

The proposed methodology tries to address these issues by exploiting Genetic control Algorithm (GA) and Equivalent Consumption Minimization Strategy (ECMS) [22], [25] for definition of the hybrid architecture and powertrain control strategy, respectively. The following section will go deeper in the description of these approaches, providing also some more details about the selected control techniques.

3. Optimal design methodology of a plug-in HEV

The proposed methodology can be divided into three layers, as shown in Fig. 1: Genetic Algorithms (GAs) optimization, hybrid powertrain model and the EMS. The GAs optimization layer evaluates every possible individual hybrid powertrain model for each generation, and then it determines the optimal solution in the current generation. Besides that, it also controls the evolution from the current generation to the following one according to its dedicated operators. The less suitable powertrain models in terms of fitness function in the current generation are substituted by the new generated powertrain models for the following generation. The final solution of optimal design problem is determined by the hybrid powertrain model which evaluates the fuel consumption over a certain driving cycle through a backward approach. Finally, the EMS, as the core of the hybrid powertrain model, controls the energy consumption and thus the final CO_2 emissions over a certain driving cycle. In order to achieve the optimal control of the on board energy sources for a specific hybrid powertrain, the Equivalent Fuel Consumption Minimization Strategy (ECMS) is chosen as the online energy management strategy of the powertrain model. The optimality of the energy management strategy is reached by tuning the equivalent factors [22], [25] of the ECMS.

In the next section more details about the GAs, the powertrain control strategy and the vehicle modeling approach will be provided.

3.1. Genetic algorithms

Genetic Algorithms (GAs) [13] are adaptive heuristic search methods that mimic the natural biological evolutionary idea of natural selection and genetics. They present an intelligent exploitation of a random search to solve optimization problems. Despite randomized, GAs use historical knowledge to direct the search into the region of better performance within the search space. The main strengths of GAs to optimize the hybrid powertrain design characteristics can be summarized as follows [4]:

- GA is a global search method, since it operates along a population of points in parallel but not on a single point.

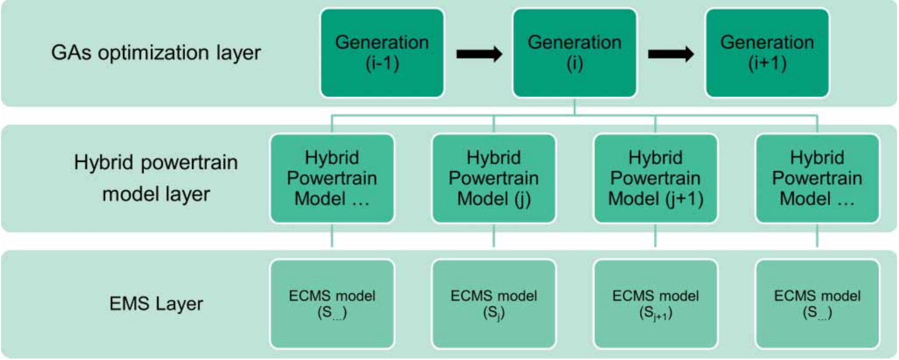

Figure 1. Hierarchy of the proposed methodology.

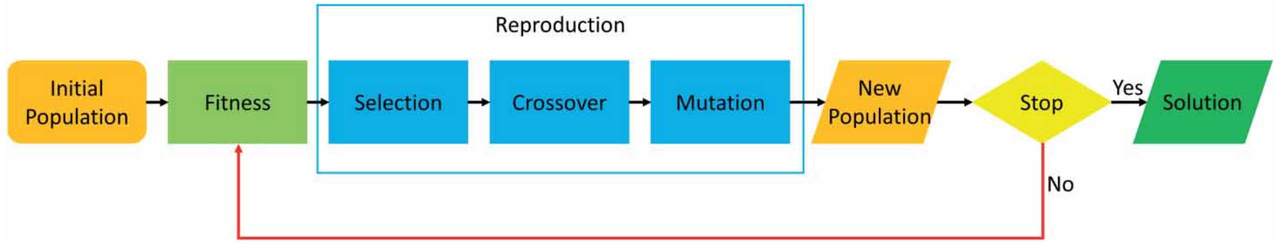

Figure 2. Flow chart of GAs.

- Simplicity for application, since there are not requirements about the derivative information or other auxiliary knowledge.
- GA uses probabilistic transition rules instead of deterministic ones.
- GA works on an encoding of parameter set rather than on the parameter set itself.

The general working flow of GAs is depicted in Fig. 2. Starting from an initial population, possible solutions of the optimization process are randomly generated, selecting candidates within the design domain. One possible solution in a population is called "individual" and, in this case, it represents a certain hybrid powertrain architecture (series or parallel), with a certain ICE, a battery pack, an electric motor, an electric generator and a specified EMS. Each individual is encoded through a binary number (gene in GAs) into a parameter set named chromosome. Then the performance of all the individuals of the initial population has to be assessed through the objective function.

The objective values are converted into the relative fitness values, which are responsible for the amount of offspring that an individual can expect to produce in the next generation. Indeed the compatibility of each individual is determined by its corresponding fitness.

Then, the algorithm evolves through three operators in the reproduction step:

- Selection, which equates to survival of the fittest;
- Crossover, which represents mating between individuals;
- Mutation, which introduces random modifications to avoid local convergence.

The key idea for the selection operator is to give the preference to best individuals, allowing them to pass their genes to the next generation. The effectiveness of each individual depends on its fitness value, which is assessed via the fitness operator. The common selection operators include the roulette wheel selection methods and the stochastic universal sampling method.

The prime distinguished factor of GAs from other optimization techniques is the crossover operator, which produces new chromosomes for the next generation. Like its counterpart in nature, crossover produces new individuals, which have some parts of both parents' genetic material. The typical crossover operators can be clustered as single-point crossover, multi-point crossover, uniform crossover and other crossover operators such as shuffle operator, reduced surrogate operator and so on.

The purpose of the mutation operator is to maintain the diversity within the population and inhibit premature convergence. With some low probability, typically in the range 0.001 and 0.01, a portion of the new individuals will have some of their bits flipped. It is a completely random process, which modifies elements in the chromosomes.

Once a new population has been produced by selection, crossover and mutation, the fitness of the individuals in the new generation has to be determined. According to the size of new individuals there could be a generation gap, which means the fractional difference between the new and old population sizes. To maintain the size of the original population, the offspring individuals have to be reinserted into the parental population. When selecting which members of the old population should be substituted, the apparent strategy is to replace the least fit members deterministically.

It is difficult to specify the convergence criteria because the GA is a stochastic search method. A common practice is to terminate the GA after a pre-specified number of generations and then test the quality of the best members of the population against the problem definition.

3.2. Equivalent consumption minimization strategy

In the Equivalent Consumption Minimization Strategy (ECMS) the global optimization problem of the identification of the most efficient usage of the energy stored on board of a hybrid electric vehicle is reduced to a local optimization problem, solved at each instant of time [21]. This strategy is based on the concept that in a hybrid vehicle the usage of the electric power can be associated with an equivalent fuel consumption. The equivalent future fuel consumption, which will be needed to recharge the battery, whenever the electric power is used for vehicle propulsion, can be summed to the present real fuel consumption to obtain the instantaneous equivalent fuel consumption:

$$m_{eqv} = m_f + m_{batt} = m_f + s\frac{P_{batt}}{LHV} \quad (1)$$

where m_f is the engine instantaneous fuel consumption (expressed as mass flow rate), LHV is the fuel Lower Heating Value (energy content per unit of mass), m_{batt} is the virtual fuel consumption associated with the use of the electrical rechargeable energy storage system, P_{batt} is the power delivered by the electric actuator(s) and s is an equivalence factor. This latter parameter is representative of the future efficiency of the battery recharge, i.e. it translates into an equivalent fuel consumption the usage of the electrical energy stored into the battery. As a result, the ECMS implicitly relies on some information about future driving conditions in order to tune the equivalence factor and fully exploit the hybridization potential.

3.3. Simulation tools

All the analysis presented in this paper were carried out through numerical simulations performed on a vehicle model developed in Matlab environment. It relies on a kinematic approach [17] based on a backward methodology, where the input variables are the speed of the vehicle and the grade angle of the road. From these variables, the powertrain output speed and the traction force, which should be provided to the wheels, can be easily determined. Both the internal combustion engine and the electric machines are represented through performance maps, which were experimentally measured under steady state operating conditions. Despite the simple approach, other works proved good agreement [16] in the calculation of the instantaneous fuel consumption over the most common regulatory driving cycles.

4. Case study architecture

4.1. Features of the vehicle

Nowadays light duty commercial vehicles are significant sources of pollution especially within urban areas, where they also represent about one fourth of CO_2 emissions coming from transport activities [1]. Public Governments are therefore currently trying to regulate the access of freight within city centers, introducing restrictions related to environmental criteria and road pricing [24], [6]. In such a framework vehicle hybridization could represent a valuable solution for delivery companies to be compliant with public regulation and also to reduce their expenditure in fuel, which from a strictly economic perspective, represents a significant portion of their budget.

Table 1. Main Feature of the case study light commercial vehicle

Weight (full load) [kg]	$\approx$ 2000
Traction Power [kW] necessary @ 100 km/h	19.5
Front area [m^2]	3.2
Rolling resistance coefficient [kg/ton]	11.2
Transmission ratios for parallel plug-in HEV	[3.72 2.13 1.32 0.89 0.67]
Final drive transmission ratio for parallel plug-in HEV	4.19

Therefore a light duty commercial vehicle was selected as a case study to prove the effectiveness of the proposed design methodology. The main features of the considered application are listed in Tab. 1.

In order to define the vehicle layout, which maximizes the hybridization benefit for this kind of application, in this analysis a series architecture, Range Extended [10], [23] and a parallel Through the Road (TTR) architecture were selected (see Fig. 3) [28], [3].

Concerning the Electric Machine an Interior Permanent Magnet (IPM) electric machine was chosen because of its compact design and high efficiency.

Tab. 2 shows the power levels for the electric machines considered in the optimization process. These configurations could be obtained by increasing the number of modules of the electric machine (see the scheme of the IPM electric motor/generator in Fig. 4) and scaling its efficiency map accordingly to power level reached (see Fig. 5(a)).

The electric machine is powered by a Li-Ions battery pack, the energy and power of which can be varied acting on the number of cells or on their characteristics (see Tab. 3).

Then, since in a hybrid powertrain the main driver orienting the choice of the internal combustion engine is typically the downsizing, 6 different possible ICEs were selected for this analysis (see Tab. 4), starting from the features of a 1.2 liter Diesel Engine already available on the market, which was selected as the "base" engine (the Brake Specific Fuel Consumption, BSFC, map of which is shown in see Fig. 5(b)).

Finally, as far as the energy management of the hybrid powertrain is concerned, in this study an EMS featuring a combination of pure EV and Charge Sustaining modes was implemented, in order to allow both zero emission operations within LEZ and satisfactory range capabilities for connections with dock terminals located in suburban areas. Such an approach was proved to be capable to achieve suboptimal performance [26], [18] and to guarantee the charge balance of the battery by means of a selection of a proper equivalence factor in the Equivalent Consumption Minimization Strategy (ECMS) adopted for the energy management.

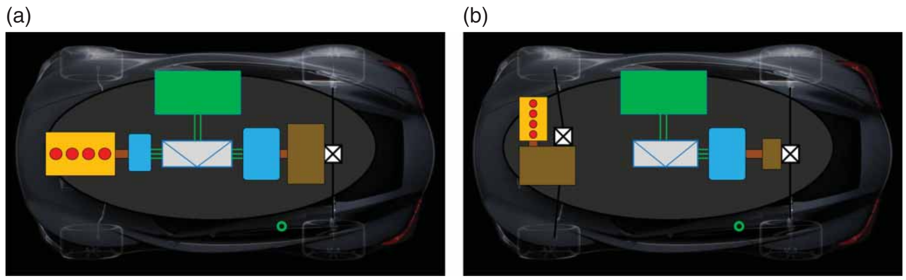

Figure 3. Hybrid architectures considered in the design process: – (a) series architecture; (b) parallel Through the Road architecture.

Table 2. Design matrix for the Electric Motor Generator.

	EMG 1	EMG 2	EMG 3	EMG 4	EMG 5
Weight [kg]	39	47	51	59	68
Peak power [kW]	35	46	53	70	88
Base speed [rpm]	12000	–	–	–	–
Max. speed [rpm]	3350	–	–	–	–

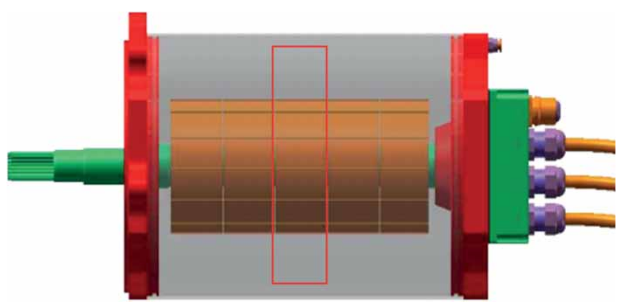

Figure 4. Scheme of the IPM electric motor/generator: thanks to its modular design, different rated power values can be obtained by means of different rotor modules (one of which is highlighted in red).

4.2. Problem formulation

As already pointed out in Section 4.1, the main target of the hybridization of a light duty commercial vehicle is the reduction of its fuel consumption or, in other words, of its CO_2 emissions. Thus the proposed methodology aims to minimize the performance index described in Eq. 2:

Table 3. Main features of the Battery Cells.

	31Ah Cell	40 Ah Cell
Cell technology	Lithium-ion polymer	
Nominal capacity [Ah]	31	40
Nominal voltage [V]	3.7	3.7
Max. cont. discharge current [A]	155	320
Max. cont. charge current [A]	62	120
Weight [kg]	0.705	1.03

Table 4. Design matrix for the Internal Combustion Engine ICE.

	ICE 1	ICE 2	ICE 3	ICE 4	ICE 5	ICE 6
Cylinders	2	2	4	3	3	4
Displacement [L]	0.8	1.0	1.2	1.5	1.8	2.4
Rated power [kW]	37	46	55	69	82.5	110

$$J = \frac{\mu_{CO2}}{\mu_{fuel}} \int_0^T \dot{m}_f(t, u(t))dt + f(p) \qquad (2)$$

Where J is the cost-to-go function, μ_{CO2} and μ_{fuel} are the molar mass of CO_2 and fuel respectively, m_f is the instantaneous fuel consumption of the engine, *u(t)* is the vector of the control variables, T is the duration of the vehicle mission and *f(p)* is a penalty function, which decides

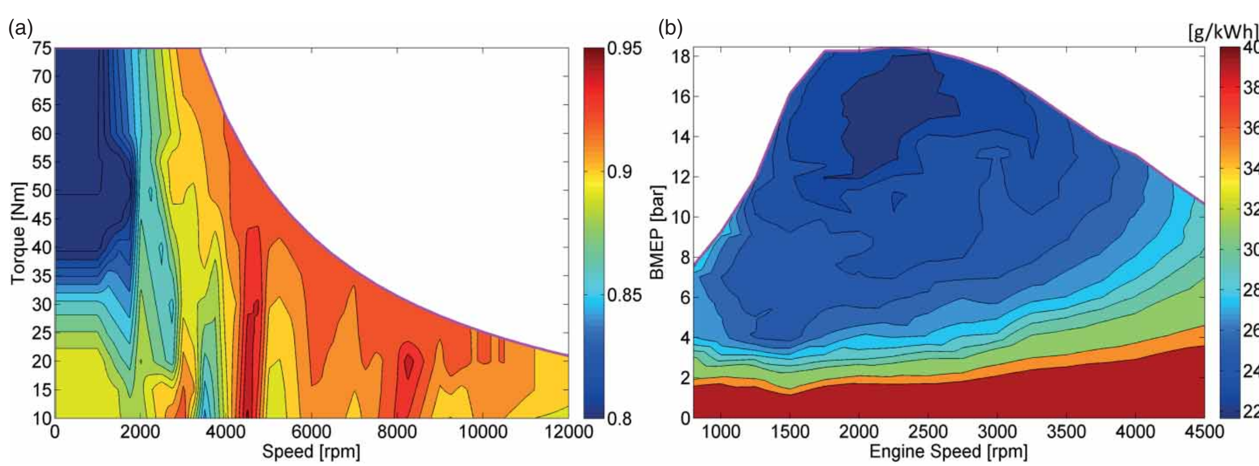

Figure 5. Characteristics of the electric motor and of the internal combustion engine: - (a) the efficiency map of the base IPM; (b) the brake specific fuel consumption map of the base engine.

about the survival of proper individuals in each generation and denies the improper solutions of the candidates. The performance index therefore evaluates the fitness of the individuals on the basis of their CO_2 emissions, and of a penalty function which is effective when the individual chromosome violates one of the following constraints.

1. **Maximum power (electric motor/generator): t**he electric motor/generator has to be able to meet the instantaneous power requirement of the EMS in a well-controlled thermal condition, i. e.:

$$f_1(p) = |(|P_{emg,req}(t)| - P_{emg,max}(t))|dt \tag{3}$$

Where $P_{em,req}$ is the instantaneous power request to the electric motor/generator and $P_{em,max}$ is the maximum available power from the electric motor/generator.

2. **Maximum power (battery):** at each time instant the power requested to the battery should be within its limits, i.e.:

$$f_2(p) = |(|P_b(t)| - P_{b,max}(t))|dt \tag{4}$$

Where P_b is the instantaneous power requirement to the battery and $P_{b,max}$ the instantaneous maximum available power of the battery.

3. **Energy of the battery:** in order to achieve the desired AER the battery pack should have enough energy. According to the TNO report [27], the daily mileage of a European light-duty commercial vehicle is about 94 km/day, the 43% to 53% of which is travelled within urban areas. Thus, an AER of 45±5 km was set as the target for the tested vehicle, thus leading to the following penalty function:

$$f_3(p) = |(E_b - E_{AER})| \tag{5}$$

where E_{AER} is the desired battery energy to fulfill the requirement of the AER and E_b is the total energy of the battery.

4. **Final battery SOC:** since the powertrain control strategy will be optimized in charge sustaining operation, at the end of the mission profile the vehicle has to achieve a neutral energy balance, with a State Of Charge (SOC) variation compared to the initial value which should be smaller than 1% of the chemical energy consumed during the driving cycle, i.e.:

$$f_4(p) = |(SOC_0 - SOC_{end})| \tag{6}$$

where SOC_0 and SOC_{end} are the initial and the final SOC of the mission profile.

In conclusion, the penalty function is the sum of each contribution described before (See Eq.7).

$$f(p) = c_1 f_1(p) + c_2 f_2(p) + c_3 f_3(p) + c_4 f_4(p) \tag{7}$$

Where c_1, c_2, c_3 and c_4 are the coefficients needed to convert the different penalty functions into the same unit.

Although the minimization of the cost function should ideally consider the entire life cycle of the vehicle, nevertheless, in practical cases, the optimization horizon is finite and usually coincides with a short trip. In this case the analysis was focused on the Worldwide Harmonized Light Duty Driving Cycle (WLTC) [12], whose city section (see Fig. 6) was used to evaluate the All Electric Range of the vehicle: since the distance covered during the city section of WLTC is just a fraction of the target AER, it was assumed that the vehicle would repeat the WLTC city section until reaching the target AER.

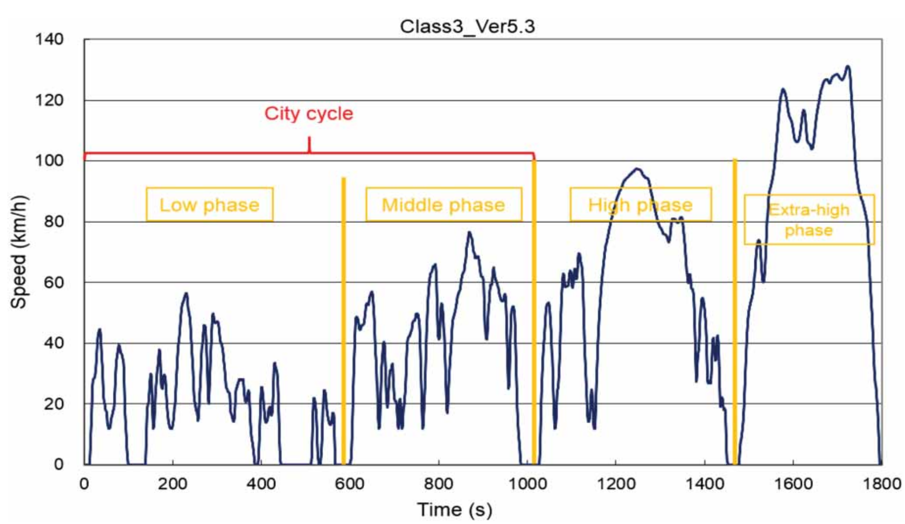

Figure 6. Worldwide Harmonized Light Duty Driving Cycle – Class 3.

5. Simulation results

The evolutionary traces of the key factors, such as cost function values for CO_2 emissions, AER and final SOC, are illustrated in Fig. 7. It is eye-catching that the cost function (Fig. 7.a) becomes stable after 25 generations because all the constraints work effectively. On the other hand, the specific CO_2 emission of each generation was stabilized after 50th generation according to Fig. 7.b. The comparison between the top figures manifests the difference between the cost funtion value and the real specific CO_2 emissions, which results from the penalties due to the violation of constraints set in section 4.2. When all of the constraints are respected, the specific CO_2 emission become identical to the cost function value for the last tens of generations.

Furthermore, the AER, as reported in Fig. 7.c, shows a convergence at a very low pace if compared with the other quantities. The reason is related to the more relaxed constraint, which has less tight limitations than the others (AERs from 40 to 50 km are considered as acceptable). On the contrary, the final SOC of the battery is strictly constrained, since the target is to keep the hybrid powertrain in the charge-sustaining mode.

The optimal hybrid powertrain determined by the algorithm was taken from the last generation after it reached the stable condition as shown in Fig. 7. The main features of the optimized powertrain are listed in Tab. 5.

For this application the parallel architecture was selected by the GA due to its higher flexibility and efficiency. The strongly downsized diesel engine and the smallest power level of electric motor were chosen, thus achieving the specific CO_2 emissions of 133 g/km. The CO_2 reduction compared to the conventional vehicle, equipped with a 1.2L diesel engine, is about 22%.

The 40Ah battery cell was selected with 72 battery cells in total. Compared to the other battery cell, it has smaller energy density but better power density since the maximum discharge current allowed is much higher than the 31 Ah cell. Finally, the optimization of the ECMS was achieved through the selection of two equivalent factors *s* (one for the battery discharging phases, the other for the battery charging phases).

The stability of this configuration was confirmed by the analysis of the last fifty generations where the powertrain was uniquely in parallel configuration, featuring the 2 cylinder 0.8L ICE and the 40Ah battery cell.

The performance of this optimized plug-in hybrid powertrain are summarized in Tab. 6, while the main

Table 5. Optimal sizing solution.

Architecture		Parallel
ICE		ICE 1 (2 cyl. 0.8L 37 kW)
Electric motor/generator		EMG 1 (35 kW)
Battery	cell type	40Ah cell
	cell number	72
ECMS	s_{dis}	3.45
	s_{chg}	2.29

Table 6. Main performance of the optimized plug-in HEV.

Desired AER [km]	50 ± 5
Real AER [km]	49
Battery energy [kWh]	11
Full load vehicle mass [kg]	1950
Specific CO_2 emission [g/km]	133

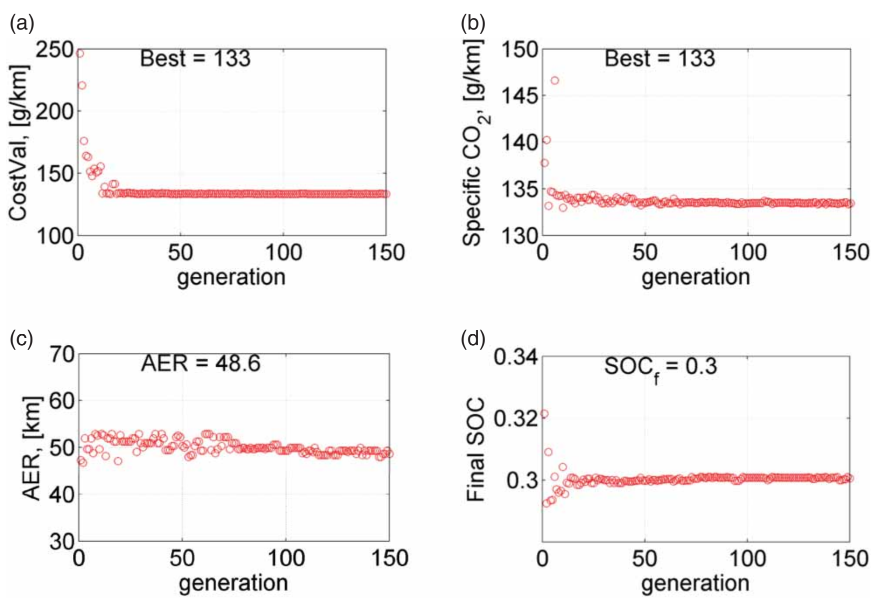

Figure 7. The evolution traces of the GAs optimization methodology. From left to right and top to bottom: (a) cost function value, (b) specific CO_2 emissions, (c) All-Electric-Range, (d) final battery SOC.

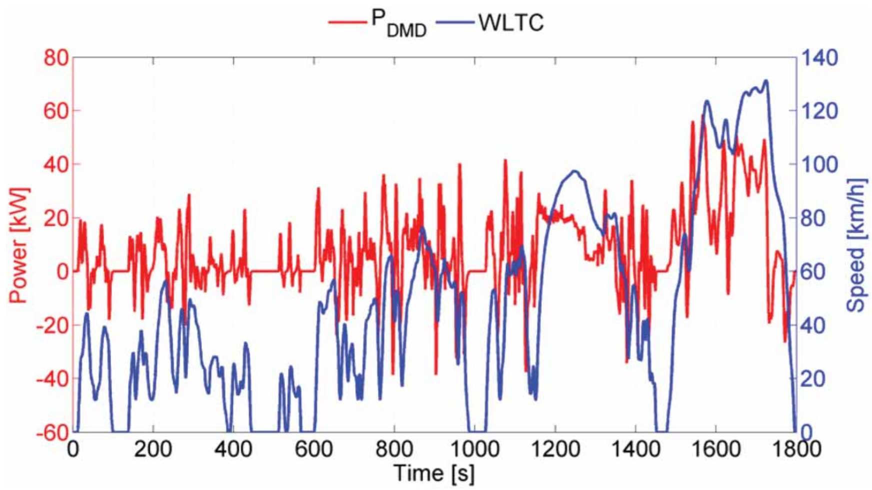

Figure 8. Power demand for the optimal powertrain (red line) and vehicle speed (blue line) over the WLTC.

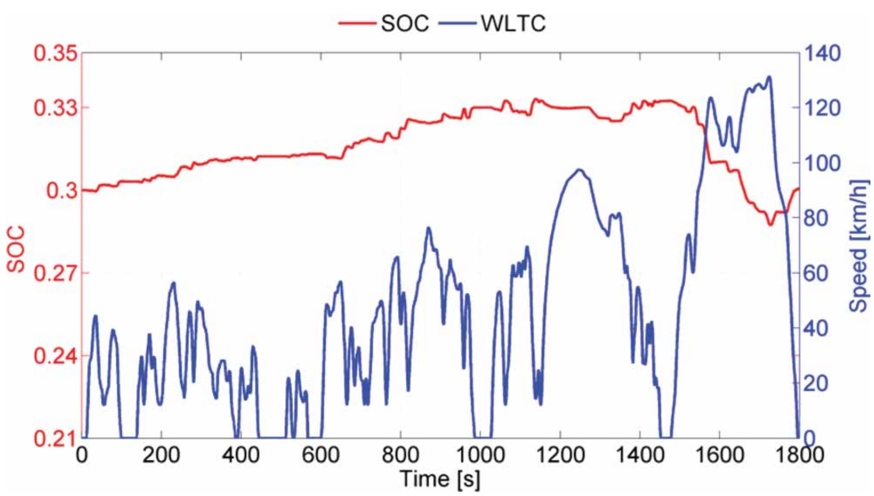

Figure 9. Battery SOC profile (red line) and vehicle speed (blue line) over the WLTC.

details about its operating characteristics are reported in Fig. 9 to 12.

The power demand over the WLTC is shown in Fig. 8. According to the ECMS, the power demand has been split into two parts, one provided by the diesel engine, the other provided by the electric motor. The SOC of the battery profile, shown in Fig. 9, results from the instantaneous power of the electric motor/generator: it can be noticed that, in order to minimize CO_2 emissions, the battery has to store energy during the first three phases, to be then depleted during the extra-high phase, thus guaranteeing the charge sustaining condition.

The power delivered by the ICE, by the electric motor/generator EMG and their sum are shown in Fig. 10. It can be noticed that the ICE power is almost coincident with the sum of the ICE and of the EMG power. It means that during the traction phases the ICE is the prime power source, while the electric motor/generator only assists the ICE to reach the best fuel economy performance.

Finally the operating points of the ICE are shown on the Brake Specific Fuel Consumption map (BSFC) reported in Fig. 11. It can be noticed that the operating points of the ICE are mainly concentrated in the high efficiency (or low fuel consumption) area, which is a consequence of the ECMS optimization. Moreover, since the optimal ICE size selected by the GA is significantly downsized, it can be noticed that the engine has to be not infrequently operated at full load condition over the WLTC.

5.1. Sensitivity analysis

Finally a sensitivity analysis was carried out in order to assess the robustness of the proposed methodology.

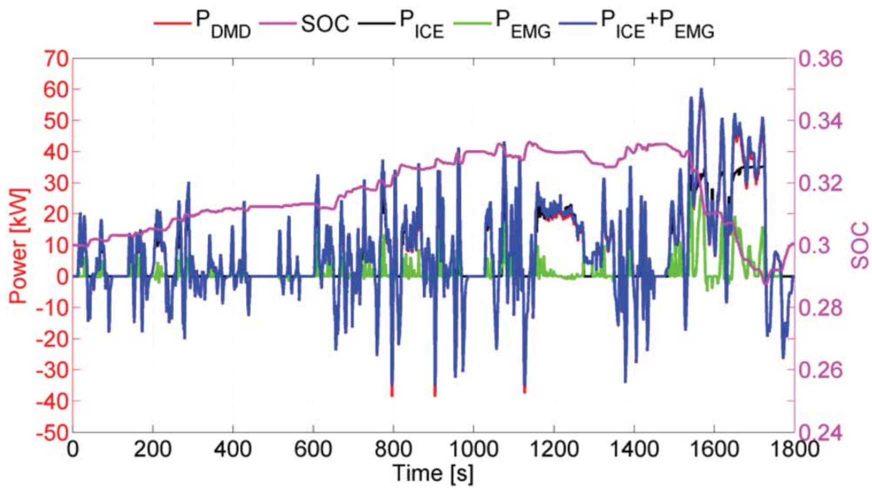

Figure 10. Power demand (red line), power delivered by the ICE (black line), power delivered by electric motor/generator EMG (green line) and sum of ICE and EMG power (blue line) over the WLTC.

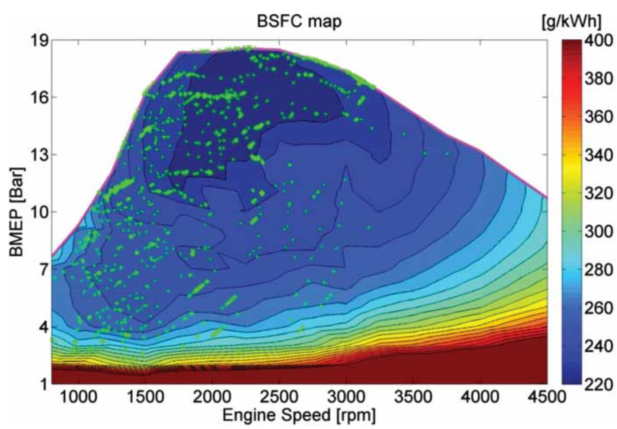

Figure 11. Operating points of ICE on the Brake Specific Fuel Consumption (BSFC) map.

Table 7. Comparison between optimal powertrain solutions for different powertrain architectures.

Architecture		Parallel	Series
ICE		ICE 1 (2 cyl., 0.8L, 37 kW)	ICE 2 (2 cyl., 1.0L, 46 kW)
Electric motor/generator		EMG 1 (35 kW)	EMG 4 (70 kW)
Battery	cell type	40Ah cell	40Ah cell
	cell number	72	80
ECMS	s_{dis}	3.45	4.48
	s_{chg}	2.29	2.29
Results	CO_2 Emissions	133 g/km	143 g/km
	AER	49 km	52 km

5.1.1. HEV architecture

Firstly, a series architecture was considered as an alternative to the parallel architecture which was selected through the GA. The results of the optimization process carried out on the series architecture are shown in the following Tab. 7 where they are compared to the fully optimized hybrid powertrain (which has a parallel architecture).

The series architecture features a more powerful electric motor, since it has to propel the vehicle continuously and not only to support the ICE during high power demanding phases. As a consequence, also the size of the engine and the energy of the battery pack have to be increased in order to allow the exploitation of the maximum power of the EM with a similar AER (see Tab. 7). Concerning the CO_2 emissions the optimized series plug-in HEV achieves 143 g/km which is 7.5% worse than the globally optimized solution.

5.1.2. Internal combustion engine

Even if the size of the ICE should be optimized depending on the mission of the vehicle, in practical cases only limited power levels are available. Therefore in this analysis only the reference engine which was already available on the market (i.e. ICE #3, 1.2 liter displacement) was considered in order to point out the effects of the ICE size on the hybrid powertrain performance.

Results of the optimal components for the 1.2 L ICE #3 case were then compared with the global optimal solution in Tab. 8. It can be noticed that the solution for the 1.2 L ICE #3 case does not differ so much from the global optimal solution. The specific CO_2 emission of the 1.2 L ICE #3 engine powertrain is only about 2% higher than the globally optimized hybrid powertrain (135 g/km), while a slightly smaller battery can be used in combination with the larger displacement of the ICE, although this leads to a shorter AER.

In conclusion the proposed methodology appears to be capable of effectively identifying the optimal powertrain components size from the early stage of the design process.

Table 8. Comparison between optimal powertrain solutions for different ICE sizes.

Architecture		Parallel	parallel
ICE		ICE 1 (2 cyl., 0.8L, 37 kW)	ICE 3 (4 cyl., 1.2L, 55 kW)
Electric motor/generator		EMG 1 (35 kW)	EMG 1 (35 kW)
Battery	cell type	40Ah cell	40Ah cell
	cell number	72	70
ECMS	s_{dis}	3.45	2.68
	s_{chg}	2.29	2.81
Results	CO_2 Emissions	133 g/km	135 g/km
	AER	49 km	47 km

6. Conclusions

In this paper a comprehensive methodology to optimally design a hybrid electric powertrain from the early stages of the process was presented.

The methodology is based on the genetic algorithm approach for the choice of the powertrain component characteristics, combined with a quasi-optimal energy management strategy, the Equivalent fuel Consumption Management Strategy (ECMS). The performance of the hybrid electric powertrain which was designed through the proposed methodology were then assessed and analyzed over the Worldwide Harmonized Light Duty Driving Cycle (WLTC) by means of a simulation model, thus demonstrating its effectiveness in addressing the issue of the powertrain components sizing from the early stage of the design process.

The main findings of this study can be summarized as follows:

- the Genetic Algorithm exploited in the design process of a hybrid light duty commercial vehicle was proved to be capable to identify the best configuration and the best powertrain component characteristics that minimize the fuel consumption of the vehicle;
- the robustness of the proposed methodology was also assessed through a sensitivity analysis, as far as the powertrain architecture and the size of the ICE are concerned.

Definitions/Abbreviations

AER	All Electric Range
EM	Electric Machine
EMS	Energy Management System
ECMS	Equivalent Consumption Minimization Strategy
ECU	Engine Control Unit
GA	Genetic Algorithm
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
IPM	Interior Permanent Magnet
LHV	(Fuel) Lower Heating Value
PID	Proportional Integral Derivative
RB	Rule Based
EV	Electric Vehicle
SOC	State of Charge
LEV	Low Emission Zone
pHEV	plug-in Hybrid Electric Vehicle
TTR	Through The Road
WLTP	Worldwide harmonized Light duty vehicles Test Procedure

ORCID

Federico Millo http://orcid.org/0000-0002-3540-5564
Jianning Zhao http://orcid.org/0000-0003-4072-3791
Luciano Rolando http://orcid.org/0000-0001-7695-698X
Claudio Cubito http://orcid.org/0000-0003-4767-6975
Rocco Fuso http://orcid.org/0000-0002-9138-9490

References

[1] Albergel, A.; Segalou, E.; Routhier, J-L.; De Rham, C.: Méthodologie pour un bilan environnemental physique du transport de marchandises en ville, ADEME, 2006.
[2] Bianchi, D.; Rolando, L.; Serrao, L.; Onori, S.; Rizzoni, G.; Al-Khayat, N.; Hsieh, T.-M.; Kang, P.: A rule-based strategies for a series/parallel hybrid electric vehicle: an approach based on Dynamic Programming, ASME 2010 Dynamic Systems and Control Conference, vol. 1, pp. 507–514, 2010, http://dx.doi.org/10.1115/DSCC2010-4233.
[3] Bianchi, D.; Rolando, L.; Serrao, L.; Onori, S.; Rizzoni, G.; Al-Khayat, N.; Hsieh, T.-M.; Kang, P: Layered Control Strategies for Hybrid Electric Vehicles Based on Optimal Control, International Journal of Electric and Hybrid Vehicles, vol. 3, no. 2, pp. 191–217, 2011, http://dx.doi.org/10.1504/IJEHV.2011.042147.
[4] Chipperfield, A.; Fleming, P.; Pohlheim, H.; Fonseca, C.: Genetic Algorithm Toolbox for Use with MATLAB, Department of Automatic Control and Systems Engineering, University of Sheffield, 1994.
[5] Cisternino, M.; Paladini, V.; Cipolla, G.; Millo, F.; Badami, M.; Mafrici, G., Rizzoni, G.; Miotti, A.: From Micro to Full, exploiting the benefits of different degrees of hybridization in a flexible hybrid architecture, 19th International AVL Conference Engine & Environment, 2007.
[6] Dablanc, L.: Freight Transport for Development Toolkit: Urban Freight, Transport Research Support, World Bank, 2009.
[7] Ebbesen, S. B.: Optimal sizing and control of hybrid electric vehicles, ETH Institute for Dynamic Systems and Control, 2012, http://dx.doi.org/10.3929/ethz-a-007580109.
[8] Finken, T.; Felden, M.; Hameyer, K.: Comparison and design of different electrical machine types regarding their applicability in hybrid electrical vehicles, 18th International Conference on Electrical Machines, pp. 1, 5, 6–9, 2008, http://dx.doi.org/10.1109/icelmach.2008.4800044.
[9] Galdi, V.; Ippolito, L.; Piccolo, A.; Vaccaro, A.: A genetic-based methodology for hybrid electric vehicles sizing, Soft Computing, vol. 5, iss. 6, pp. 451–457, 2001, http://dx.doi.org/10.1007/s005000100129.
[10] Genender, P.; Wolff, K.; Eisele, G.; Jung, G.: NVH Development of an Electric Vehicle with Range Extender Unit,

International conference on NVH of hybrid & electric vehicles, Supméca, Saint-Ouen, France, 2010, paper R-07.03.2010.

[11] Guzzella, L.; Sciaretta, A.: Vehicle Propulsion Systems Introdcution to Modeling and Optimization, Springer Berlin Heidelberg, 2007.

[12] Hieinz, S.: Homologation test cycles worldwide - Status of the WLTP, International Energy Agency, Retrieved on 30 June 2014, from http://www.iea.org/media/workshops/2013/gfeilabelling/07.08.Homologationtestcyclesworldwide.pdf.

[13] Holland, J.-H.: Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence, MIT Press, Cambridge, Massachusetts, 1992.

[14] International Energy Agency. Office of Energy Technology and R&D.: Energy technology perspectives 2010 – Scenarios & strategies to 2050, International Energy Agency, Paris, France, 2010.

[15] Millo, F.; Badami; M.; Ferraro, C.; Rolando, L.: Different Hybrid Powertrain Solutions for European Diesel passenger cars, SAE Int. J. Engines 2(2):493–504, 2010, http://dx.doi.org/10.4271/2009-24-0064.

[16] Millo, F.; Di Lorenzo, G.; Servetto, E.; Capra, A.: Analysis of the Performance of a Turbocharged S.I. Engine under Transient Operating Conditions by Means of Fast Running Models, SAE Int. J. Engines 6(2):968–978, 2013, http://dx.doi.org/10.4271/2013-01-1115.

[17] Millo, F.; Rolando, L.; Andreata, M.: Numerical simulation for vehicle powertrain development, Numerical analysis - theory and application, pp.519–540, 2011, http://dx.doi.org/10.5772/24111.

[18] Millo, F.; Rolando, L.; Mallamo, F.; Fuso, R.: Development of an Optimal Strategy for the Energy Management of a Range-Extended Electric Vehicle with Additional Noise, Vibration and Harshness Constraints, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering January 2013 227: 4–16, first published on October 12, 2012 http://dx.doi.org/10.1177/0954407012457488.

[19] Millo, F.; Rolando, L.; Servetto, E.: Development of a Control Strategy for Complex Light-Duty Diesel-Hybrid Powertrains, SAE Technical Paper 2011-24-0076, 2011, http://dx.doi.org/10.4271/2011-24-0076.

[20] Murgovski, N.; Johannesson, L.; Sjöberg, J.; Egardt, B.: Component sizing of a plug-in hybrid electric powertrain via convex optimization, Mechatronics, vol. 22, iss. 1, pp. 106–120, 2012, http://dx.doi.org/10.1016/j.mechatronics.2011.12.001.

[21] Paganelli, G.; Delprat, S.; Guerra, T.; M., Rimaux, J.; Santin, J.-J.: Equivalent consumption minimization strategy for parallel hybrid, Vehicular Technology Conference, vol.4, pp.2076–2081, 2002, http://dx.doi.org/10.1109/VTC.2002.1002989.

[22] Paganelli, G.; Tateno; M.; Brahma; A., Rizzoni; G., Guezennec, Y.: Control development for a hybrid-electric sport-utility vehicle: strategy, implementation and field test results, Proceedings of the American Control Conference, vol. 6, pp. 5064–5069, 2001, http://dx.doi.org/10.1109/ACC.2001.945787.

[23] Pischinger, M.; Wittek, K.; Genender, P.: V2-range extender module with FEVcom–a barely noticeable companion in your Electric Vehicle, *20th* Aachener Kolloquium Fahrzeug-und Motorentechnik, pp.871–893, Aachen, Germany, 2011.

[24] Schoemaker, J.; Allen, J.; Huschenbeck, M.; Monigl, J.: Quantification of Urban Freight Transport Effects *I*, BESTUFS consortium, 2006.

[25] Serrao, L.: A comparative analysis of energy management strategies for hybrid electric vehicles, Electronic Thesis or Dissertation, Ohio State University, 2009.

[26] Tulpule, P.; Marano, V.; Rizzoni, G.: Effects of Different PHEV Control Strategies on Vehicle Performance, 2009 American Control Conference, pp.3950–3955, 2009, http://dx.doi.org/10.1109/ACC.2009.5160595.

[27] Verbeek, M.; Smokers, R.; Schroten, A.: Assessment of Alternative Targets and Modalities for the CO_2 Regulation for Light Commercial Vehicles, TNO report, 2012. Retrieved on 6 April 2014, from http://www.transportenvironment.org/sites/te/files/TNO%202012%20Vans%20report.pdf.

[28] Young, M.; Molen, G.-M., Oglesby, D.; Crawford, K.; Walp, K.; Lewis, R.; Whitt, C.; Phillips, S.: The Design and Development of a Through-the-Road Parallel Diesel Electric Hybrid, Vehicle Power and Propulsion Conference, pp.511–518, 2007, http://dx.doi.org/10.1109/VPPC.2007.4544178.

[29] Zeraoulia, M.; Benbouzid, M.-E.-H.; Diallo, D.: Electric Motor Drive Selection Issues for HEV Propulsion Systems: A Comparative Study, IEEE Transactions on Vehicular Technology, vol. 55, pp. 1756–1764, 2006, http://dx.doi.org/10.1109/TVT.2006.878719.